AD
A078941

END
DATE
FILMED
I-80
DDC

1.0

1.1

1.25 1.4 1.6

2.8 2.5

3.2 2.2

3.6

4.0 2.0

1.8

4.5
5.0
5.6
6.3

MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

LEVEL

social science research institute

RESEARCH REPORT

RANK WEIGHTING IN MULTIATTRIBUTE
UTILITY DECISION MAKING: AVOIDING
THE PITFALLS OF EQUAL WEIGHTS

WILLIAM G. STILLWELL
WARD EDWARDS

SEPTEMBER, 1979

SSRI RESEARCH REPORT 79-2

80 1 7 083

Social Science Research Institute
University of Southern California
Los Angeles, California 90007
(213) 741-6955

INSTITUTE GOALS:

The goals of the Social Science Research Institute are threefold:

- To provide an environment in which scientists may pursue their own interests in some blend of basic and methodological research in the investigation of major social problems.

- To provide an environment in which graduate students may receive training in research theory, design and methodology through active participation with senior researchers in ongoing research projects.

- To disseminate information to relevant public and social agencies in order to provide decision makers with the tools and ideas necessary to the formulation of public social policy.

HISTORY:

The Social Science Research Institute, University of Southern California, was established in 1972, with a staff of six. In fiscal year 1978-79, it had a staff of over 90 full- and part-time researchers and support personnel. SSRI draws upon most University academic Departments and Schools to make up its research staff, e.g. Industrial and Systems Engineering, the Law School, Psychology, Public Administration, Safety and Systems Management, and others. Senior researchers have joint appointments and most actively combine research with teaching.

FUNDING:

SSRI Reports directly to the Executive Vice President of USC. It is provided with modest annual basic support for administration, operations, and program development. The major sources of funding support are federal, state and local funding agencies and private foundations and organizations. The list of sponsors has recently expanded to include governments outside the United States. Total funding has increased from approximately $150,000 in 1972 to almost $3,000,000 in the fiscal year 1978-1979.

RESEARCH INTERESTS:

Each senior SSRI scientist is encouraged to pursue his or her own research interests, subject to availability of funding. These interests are diverse: a recent count identified 27. Four major interests persist among groups of SSRI researchers: crime control and criminal justice, methods of dispute resolution and alternatives to the courts, use of administration records for demographic and other research purposes, and exploitation of applications of decision analysis to public decision making and program evaluation. But many SSRI projects do not fall into these categories. Most projects combine the skills of several scientists, often from different disciplines. As SSRI research personnel change, its interests will change also.

RANK WEIGHTING IN MULTIATTRIBUTE
UTILITY DECISION MAKING: AVOIDING
THE PITFALLS OF EQUAL WEIGHTS

Research Report 79-2

William G. Stillwell
and
Ward Edwards

Social Science Research Institute
University of Southern California

SUMMARY

The notion of "dominance" in multiattribute utility decision contexts leads to a change in the considered alternative set. The implications of this set change are discussed in relation to the conditions of Wainer's (Wainer, 1976) "equal weights theorem" and the resulting sensitivity to weighting of importance dimensions demonstrated. Data from three multiattribute decision making studies are examined using four rank weighting techniques as well as equal weights. Rank weighting of importance dimensions demonstrate marked improvement of approximation as reflected in both Pearson and rank order correlations for measures of overall utility across alternatives within the nondominated subset. Implications for multiattribute utility application are discussed.

i

TABLE OF CONTENTS

TABLES

ACNKOWLEDGEMENTS

This research was supported by the Advanced Research Projects
Agency of the Department of Defense and was monitored by the
Office of Naval Research under Contract #N00014-79-C-0038.

DISCLAIMER

The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the Advanced Research Projects Agency or of the United States Government.

1.   Introduction

A number of recent articles have compared equal weighting to
various statistical weighting schemes for linear prediction and de-
cision models (Dawes and Corrigan, 1974; Newman, 1977; Newman, Seaver,
and Edwards, 1976). Dawes and Corrigan's (1974) seminal article pro-
vided evidence that simplified weighting procedures are strikingly
robust. Both equal and random weighting procedures provided excellent
approximations to a defined optimal set of weights in such diverse
settings as graduate admissions, psychiatric diagnosis, and an ab-
stract decision task.

Expanding this notion, Einhorn and Hogarth (1975) derived the
minimum correlation between standard linear regression and unit weight-
ing composites as a measure of the degree of similarity of those com-
posites and in conclusion stated "The minimum is high for most applied
situations." They contend that unit weighting is a viable alternative
to standard regression methods "because unit weights: (1) are not esti-
mated from the data and therefore do not consume degrees of freedom; (2)
are estimated without error; and (3) cannot reverse the true relative
weights of the variables." In addition, of course, equal weights require
no elicitation.

Wainer (1976) took this argument one step further. In defense of his
"Equal weights theorem" Wainer showed that under "very general circum-
stances" equal weights can replace the least squares weights for the sam-
ple from which the regression weights were derived with little or no loss
in accuracy. He also showed that equal weights will hold up better than
weights derived from multiple regression when new samples are examined.

Although Wainer made some errors in the estimation of loss of ex-
plained variance (Laughlin, 1978) given his conditions, the conclusions
reached were both tenable and important. In fact, in many real prediction
situations equal weights provide remarkably good approximations to dif-
ferential weights, again measured by correlations between predictions.
Wainer's conditions are the following. (a) All predictor variables (at-
tributes) should be oriented properly; that is, for all of them, either
more should be better than less or less should be better than more. (b)
Predictor variables (attributes) should be positively intercorrelated.

The former condition is easy to ensure; an appropriate rescaling
will always solve the problem. Even peaked (nonmonotonic) functions be-
come monotonic when the nonmonotonic measure is rescaled into utility
or some other monotonic measure of desirability.

Condition B is the heart of the matter. Considered as a requirement
for prediction -- which, after all, is what correlations are intended to
do -- it is not a problem. GRE scores will correlate positively with
GPAs over a population of applicants to most graduate departments. The
same comment can be made about many, perhaps most, of the simple descrip-
tive measures that are typically used in examples by proponents of equal
weights.

But description, by itself, is not usually the point of any real-
world application of these ideas. Description is typically intended to
be useful. A description can, it seems to us, be useful only if it serves
as a basis for one or more decision. And indeed the examples used by the
proponents of equal weights are decision examples: admission to graduate
school, assignment to a psychiatric classification (with differential im-
plications for treatment), and so on.

Once we conclude that decision, rather than mere description, is our goal, a set of considerations quite different from those relevant to description alone become relevant -- even crucial. This paper examines some of those considerations and their consequences; we are looking into others. Some of the ideas of the riskless part of multiattribute utility measurement (MAUM) are very similar to those that enter into the equal-weights discussion and will be discussed briefly in this paper as they apply. (For expositions of various approaches to and applications of MAUM, see Keeney and Raiffa, (1976); Edwards, (1971; 1973; 1978).

Newman, in work done earlier but published in 1977, showed that in at least some multiattribute decision contexts equal weighting of attributes could lead to substantial changes inthe resulting evaluations. Following up Newman's earlier work, Newman, Seaver and Edwards (1976), in a simulation study, found that equal weighting led to poor selection ordering in most situations that have substantial negative correlations among pairs of dimensions. Keren and Newman (1978) demonstrated additionally that the presence of suppressor variables (defined by Conger, 1974) among dimensions could lead to marked inferiority of equal weighting to regression weighting, even for pure prediction situations.

The key factor that makes decision situations different from prediction situations is the idea of irrelevance, or domination. If a single option is to be chosen in a multiattributed contest, then only options on the Pareto frontier are admissible candidates. Dr. David Seaver, while a graduate student in this laboratory, first saw the point. Unpublished work he performed in 1973 (Note 1) demonstrated that while correlations between aggregate measures of overall utility were insensitive to model

changes (additive, multiplicative, and quasi-additive) for either an
entire set of 1000 options or the nondominated subset of 100 options,
within the nondominated subset these correlations were extremely sensi-
tive to dimension weights. Specifically, equal weights were found to
produce measures of overall utility which markedly differed from those
produced by the defined set of optimal weights.

Table 1 gives the results of this analysis. Of particular interest
are the correlations of weighting procedure 1 (the defined optimal weight

-

set) with weighting procedure 2 (differential and correctly rank ordered
but non-optimal) and weighting procedure 1 with weighting procedure 3
(equal weights). The explicit implication of this analysis is that weights
do matter when nondominated options are being considered, but are not
crucial as long as they are correctly rank ordered and to some extent
differential. Implicit in the analysis is that negative correlations
exist between dimensions within the nondominated set of alternatives. Al-
though his paper did not report this analysis, Seaver looked at the cor-
relations between dimensions within the non-dominated set of alternatives
and found that indeed many were negative. In fact 9 out of a possible 10
of these correlations for the 5 dimensions were negative. And it is these
negative correlations between dimensions that are responsible for the poor
performance of equal weights.

Following up on the insight of Seaver and the implications of his
study, the importance of which is only now beginning to be understood,

TABLE 1

Correlations between overall utilities for
Different models and weighting schemes.

		all alternatives	admissible alternatives
# alternatives		1000	100
# dimensions		5	5
Composition Rule	F_1	.980	.995
	F_2	.690	.878
	F_3	.825	.867
	F_4	.660	.504
# dimensions		5	5
Weighting procedures	1 x 2	.970	.959
	1 x 3	.752	.514
	1 x 4	.335	-.157
	1 x 5	.164	-.274
	2 x 3	.870	.692
	2 x 4	.511	.053
	2 x 5	.324	-.109
	3 x 4	.869	.757
	3 x 5	.743	.630
	4 x 5	.968	.971

1: (81, 49, 25, 9, 1) [optimal]
2: (9, 7, 5, 3, 1)
3: (1, 1, 1, 1, 1)
4: (1, 3, 5, 7, 9)
5: (1, 9, 25, 49, 81)

models
$$\overline{F1(x)} - \sum_{i=1} x_i + \sum_{\substack{i \neq j \\ j}} \sum x_i x_j$$

$$F2(x) = \sum x_i + \P x_i$$

$$F3(x) + (X_1 \cdot X_2 + X_3 \cdot X_4) \cdot X_5$$

$$F4(x) = (X_1 + X_2) \cdot X_3 + X_4 \cdot X_5$$

6

McClelland (1978) demonstrated the ubiquity of significant negative corre-
lations among dimensions in multiattribute utility applications. In ad-
dition he examined the problems that accrue from the use of equal weight-
ing of dimensions in those applications.

The argument for negative correlations among dimensions relevant
to decision is extremely straightforward. Good sense and formal argument
alike would require that, in any decision situation, the chosen alterna-
tive should not be clearly inferior to some other alternative. Option B
is clearly inferior to, or, in more technical language, is dominated by
option A if A is at least as good as B on every relevant dimension, and
definitely better on at least one. In such a situation, no reasonable
person would bother to consider option B; he would simply eliminate it
from the option set. The Pareto frontier mentioned above is simply the
highly reduced set of options that remain for consideration after domi-
nated options are eliminated.

But elimination of options inevitably changes the correlations
among all pairs of dimensions. Dimensions that may have been positively
correlated in the original option set almost inevitably become negatively
correlated in the reduced one. This means, of course, that within the
reduced option set condition B of Wainer's Equal Weights theorem is al-
most inevitably violated.

Consider the following simple example. You have decided to buy a
new car. Your options are:

TABLE 2

Alternative Set

Car 1	10	22	24	42
Car 2	37	77	99	96
Car 3	89	85	28	63
Car 4	9	10	7	51
Car 5	2	1	52	7
Car 6	36	54	32	29
Car 7	2	81	29	0
Car 8	5	91	0	0

Note: Entries for this table randomly generated

Table 3 shows the correlations between dimensions for the eight cars.

TABLE 3

Attribute correlations: complete choice set

	A_1	A_2	A_3	A_4
A_1	1.0			
A_2	.42	1.0		
A_3	.20	.06	1.0	
A_4	.57	.07	.57	1.0

All correlations are slightly to moderately positive. But several cars are dominated. For instance, car 1 has values (10, 22, 24, 42) while car 2 has values (37, 77, 99, 96). No rational person would choose car 1 when he/she could choose car 2, no matter what the weighting of the attributes.

8

Similarly car 3 dominates car 4, and 2 dominates 5 and 6. Cars 2, 3, 7, and 8 are the remaining options upon which a decision analysis would have some bearing. Table 4 shows the intercorrelations for this reduced choice set. Attribute A_2 has a high negative correlation with both A_3 and A_4 in violation of Wainer's condition B.

TABLE 4

Attribute correlations: reduced choice set

	A_1	A_2	A_3	A_4
A_1	1.0			
A_2	-.10	1.0		
A_3	.20	-.89	1.0	
A_4	.67	-.62	.84	1.0

What does this violation mean? In practice it means that if equal weights were used in multiattribute utility measurement of either additive or multiplicative types, the two negatively correlated dimensions would, to some extent, cancel each other. The magnitude of the cancellation effect would depend on the size of the correlation and on the weights of the dimensions. In the car example, assume an individual's true weights to be the following:

A_1	A_2	A_3	A_4
.4	.4	.1	.1

A linear multiattribute utility analysis of the alternative cars would yield these results:

	Total Utility	Rank
Car 2	65.10	2
Car 3	78.70	1
Car 7	36.10	4
Car 8	38.40	3

The same analysis using equal weights produces the following conflicting results:

	Total Utility	Rank
Car 2	77.25	1
Car 3	66.25	2
Car 7	28.00	3
Car 8	24.00	4

The correlation between these two sets of utilities is .90. But equal weights would lead to selection of car 2 while the decision maker's true weights would lead to the selection of car 3. The potential loss in utility calculated from the decision maker's own weights is a striking 17.3%. This paper presents a set of simplified weighting procedures that avoid the problems of equal weights and at the same time simplify the assessment task.

II. Rank Weights

Weighting procedures are usually compared on two criteria, ease of elicitation (for both subject and analyst) and numerical quality. The extremes of these dimensions are represented by equal and ratio weights. Equal weights present no elicitation problem, but the numbers

give no information for discrimination between non-dominated alternatives.
Weights that have appropriate ratio properties are the most difficult
to assess by any procedure, but provide the maximum discrimination power.
These ratio properties, essential to multiattribute utility measurement,
are implicit in the elicitation procedures reviewed and invented in the
Keeney-Raiffa book (1976), and are explicitly the basis of Edwards'
procedure (Edwards, 1973; 1977; Edwards, Guttentag and Snapper, 1975).
Newman (1977) and Newman, Seaver and Edwards (1976) discuss equal versus
ratio weights thoroughly but leave unanswered the question: How simple
can elicitation be and still give adequate representation for a good
decision?

Obviously equal weights are the simplest to assess, and in a number
of prediction contexts they have been shown to be of sufficient quality
to justify their use (Newman, Seaver, and Edwards, 1976; Dawes and Corrigan,
1974). The concern of this paper is those situations in which some level
of differential weighting is necessary, yet the difficulty of eliciting
ratio weights demands some intermediate procedure. Rank weighting provides
a simplified assessment procedure and a method of assigning weights that
does not have the limitations of equal weighting.

This paper examines four rank weighting procedures. All four fall
between equal and ratio weights both in assessment ease and in number
quality. Each derives information from the rank ordering of the attributes
in the attribute set. This information determines the weight given the
attribute in the subsequent MAUM. We have named the weighting techniques
rank sum, rank reciprocal, decision rule rank and rank exponent.

Rank sum weights are the standard rank weighting technique considered in the literature. N attributes are ranked and each attribute is weighted $(N-R_i+1)$ where R_i is the rank position of the attribute. Each weight is then normalized by $\sum_{i=1}^{N} (N-R_i+1)$ so that the weights sum to 1.0. Table 5 shows rank sum weights as well as rank reciprocal and rank exponent weights for 5 dimensions. Equal weights would, of course, assign a weight of .2 to each dimension. The problem of tied ranks among dimensions will be dicussed later.

TABLE 5

Rank weights for 5 dimensions

Dimension Rank	Rank Sum Weight	Rank Reciprocal Weignt	Rank Exponent Weight (Z=1.5)
1	.333	.438	.396
2	.267	.219	.284
3	.200	.146	.184
4	.067	.088	.035

For rank reciprocal weights, the reciprocal of an attribute's rank is taken as that attribute's weight. That is, the weights before normalization are 1, 1/2, 1/3, 1/4, and 1/5. Each weight is then normalized, as in other rank weight procedures. Decision rule rank weights require one more piece of information from the decision maker. Once he has rank ordered the attributes, he must judge the weight of the most important dimension. Then equal, rank sum, or rank reciprocal weights are used; the method of choice is that which most closely approximates the weight elicited for the first dimension.

Rank exponent weights require the same information from the subject as decision rule rank weights. The weight given the most important dimension (W) is entered into the following formula:

$$W = \frac{(N)^Z}{\sum\limits_{i=1}^{N} (N - R_i + 1)^Z} \tag{1}$$

which is then solved for Z via an iterative process. N is the number of dimensions in the ranking and R_i is the rank of the ith dimension. Once Z is known, weights for the rest of the dimensions are determined. For instance the weight for the dimension ranked third would be:

$$W_3 = \frac{(N - 3 + 1)^Z}{\sum\limits_{i=1}^{N} (N - R_i + 1)^Z}$$

Table 5 shows rank exponent weights calculated for 5 dimensions using an arbitrary Z value of 1.5.

The first step in any of these methods is to delete from the list of dimensions any dimension to which the respondent wishes to assign zero weight. Ties are permitted in all four methods. For instance, the ranks in a five-dimensional problem might be 5, 4, 2.5, 2.5, and 1.

Each of these methods is easy to apply to hierarchical multi-attribute utility structures (Value Trees). Each branch of the tree is weighted separately. We have seen no published discussion of the rather trivial arithmetic by which such separately obtained branch weights can be aggregated into final weights, combined with single-dimension utilities, and thereafter be appropriately disaggregated

to produce useful profiles showing how each option stands on each major value within the tree. Such a discussion, with a real world example, appears in Edwards (Note 2).

Rank exponent weights exhibit several interesting characteristics. $Z=0$ defines the equal weights case and $Z = 1$ defines rank sum weights. As Z increases, the set of normalized weights gets steeper and steeper. One great advantage of the procedure, considered as an approximation, is that it always gives exactly the same weight to the most important dimension that the decision maker does. This ensures that the procedure will yield a highly satisfactory approximation to the ultimate utilities from a multiattribute utility analysis.

III. Three Examples

In this section we reanalyze the data from two decision problems to which MAUM has been applied. In addition we briefly review a third reanalysis, performed by Newman in this laboratory. Each raises an interesting issues about the use of rank weighting procedures. For detailed reports of the three problems see Edwards (Note 2), where MAUM was used to evaluate the desegregation plans for the Los Angeles Unified School District, Otway and Edwards (1977), a study of siting decisions for nuclear waste disposal, and Newman (1976) where automobile selection was at issue.

III. A. Desegregation

In July, 1977, the Los Angeles Unified School District asked Edwards to design a method of analysis of various desegregation plans submitted to the Los Angeles School Board as a near-final step in the prolonged Crawford desegregation case.

Seven plans were chosen for evaluation. Unfortunately, the plan finally adopted by the board could not be among them, since it was prepared too late for evaluation.

Prolonged discussions with senior District officers, School Board members, plaintiffs and intervenors in the Crawford case, and others led to a very complex Value Tree. The tree had four levels and a total of 144 twigs. (A twig is the lowest level of a downward-branching tree; measures of performance, i.e. single-dimension utilities, must be collected for each twig). The techniques Edwards used to elicit value dimension, importance weights, and location measures (single dimension utilities), were those of SMART (Edwards 1973; 1977), suitably modified to meet the size and political requirements of the problem and the lack of decision-theoretical expertise of the numerous respondents. The most important politically necessary compromise was the use of so complex a tree. 144 twigs is far too many! But none could be eliminated without offending one or another of the very numerous stakeholders.

Eight individuals and one group judged weights, using the standard SMART ratio judgment technique. Of the eight individuals, five were members of the Board; their weights were averaged to preserve individual anonymity. The other three were desegregation experts.

The hierarchical structure of the Value Tree made such judgments possible. Judgments were made separately for each branch; the smallest branch had only two values and the largest had 14. Several techniques were used to cut down excessive judgmental labor in the lower branches of the tree.

We reanalyze only the averaged weights of the five Board members here. Each of the four rank weighting techniques, as well as equal weights, were used to calculate the overall value of each plan. In the case of rank reciprocal and rank sum weights, the number of dimensions determined the weight given to each dimension in the analysis. For decision rule rank and rank exponent weights, the weight given the most important dimension for averaged ratio weights was used to determine the complete set of individual dimension weights.

The entire analysis was conducted for each set of weights. Raw data for plan values is, of course, that used in the original analysis. The plans were examined for admissibility and none found to be dominated. Values of overall benefit were calculated for each weighting technique for both the 1978-79 and 1981-82 fiscal years. Overall benefit shows strong correspondence between results for each of the rank weighting techniques as well as equal weights. To look at the exact strength of this relationship we calculated Pearson correlation coefficients, correlating aggregate benefits of each of the seven plans as evaluated by each approximation and with actual Board weights. No correlation not involving equal weights was less than .98; no correlation involving equal weights was higher than .92.

For decision making purposes a second criterion is change in the rank ordering of alternatives by the various techniques. To examine this criterion plans were rank ordered by each weighting technique and a Kendall tau coefficient calculated. A Kendall tau coefficient repre-sents a difference between two proportions: the proportion of pairs

16

of measurements having the same relative order in a pair of rankings
minus the proportion of pairs showing different relative order in two
rankings (Hays, 1973). Thus it gives us a measure of the proportion
of changes in the rank ordering in a pair of rank ordered sets. Table
6 shows the results of this analysis for the first and second levels
of the MAUM structure.

To avoid over-interpreting Table 6 it is important to know that
all weighting procedures led to the same plan being identified as best.
Still we hope to be able to generalize to other decision problems where
a k out of N selection rather than a 1 out of N is to be made. For the
most general case the rank ordering of all alternatives is important.
If 7 graduate applicants are to be chosen out of 8 who meet the minimum
standards of selection, reversal of the rank ordering of the 7th and
8th applicants would lead to a suboptimal decision while reversal of
the 1st and 2nd ranked applicants would make no difference.

The rank order correlations in Table 6 demonstrate the clear
superiority of all rank weighting techniques to equal weights. For the
1978-79 data a loss in tau for overall utility of 23.8% (.929-.691)
results from the use of equal weights rather than the next poorest
simplification. The resultant loss for 1981-82 is 31.1% (.929-.618).
Thus, a much larger proportion of rank reversals occur with equal weights
than with any of the rank weighting techniques.

TABLE 6

Kendall tau coefficients between plan values based on ratio weights and plan values produced by approximations.

1978-79

	Equal	Rank Sum	Rank Reciprocal	Decision Rule Rank	Rank Exponent
Overall Utility	.691	.982	.929	1.000	1.000
Branch A	1.000	.982	.964	.982	1.000
Branch B	.890	.944	.815	1.000	1.000
Branch C	.929	.982	.929	1.000	.982
Branch D	.643	.982	.909	1.000	.982
Branch E	.857	.857	.929	.857	.909
Branch F	.905	1.000	1.000	1.000	1.000

1981-82

	Equal	Rank Sum	Rank Reciprocal	Decision Rule Rank	Rank Exponent
Overall Utility	.618	.929	.929	1.000	.982
Branch A	1.000	.929	.929	1.000	1.000
Branch B	.982	.982	.963	.963	.982
Branch C	.764	.982	.889	1.000	.963
Branch D	.714	.982	.982	.982	.982
Branch E	.837	.889	.909	.889	.909
Branch F	.804	.972	1.000	.972	1.000

An additional test of weighting approximation is to compare sets of weights directly. The primary difference among the various approximations is the peakedness of the weight set. Equal weights, of course, have no peak. Rank sum weights are less peaked than rank reciprocal weights. Decision rule rank and rank exponent weights are determined by the judged weight of the most important dimension. Only the rank exponent procedure (among those considered here) can produce weights more peaked than rank reciprocal.

In order to examine the relative peakness of the approximation techniques relative to the judged ratio weights, regression analyses were performed using the ratio weights as predictors of weights from each approximation technique. Slopes of the regression lines indicate the peakedness of the weights of the approximation technique relative to ratio weights. A weight set that perfectly approximates the ratio weights would result in a slope of 1.0. Table 7 shows the results of this analysis. This analysis was conducted for the highest level of

the tree as well as each second level set of weights. Equal weights have no variance and therefore the slope would equal 0.0.

Intercepts for the analyses were all virtually zero and thus are not included in this table. For the three comparisons that are possible rank exponent weights always produce slopes that rank first or second in terms of absolute distance from 1.0. This is not surprising. Rank exponent weights guarantee that the weight to the most important dimension will be correct and thus the regression analysis will have an upper end point that is anchored to the correct ratio weight. It is interesting to note that in each comparison between rank reciprocal and rank sum

18

An additional test of weighting approximation is to compare sets of weights directly. The primary difference among the various approximations is the peakedness of the weight set. Equal weights, of course, have no peak. Rank sum weights are less peaked than rank reciprocal weights. Decision rule rank and rank exponent weights are determined by the judged weight of the most important dimension. Only the rank exponent procedure (among those considered here) can produce weights more peaked than rank reciprocal.

In order to examine the relative peakness of the approximation techniques relative to the judged ratio weights, regression analyses were performed using the ratio weights as predictors of weights from each approximation technique. Slopes of the regression lines indicate the peakedness of the weights of the approximation technique relative to ratio weights. A weight set that perfectly approximates the ratio weights would result in a slope of 1.0. Table 7 shows the results of this analysis. This analysis was conducted for the highest level of

the tree as well as each second level set of weights. Equal weights have no variance and therefore the slope would equal 0.0.

Intercepts for the analyses were all virtually zero and thus are not included in this table. For the three comparisons that are possible rank exponent weights always produce slopes that rank first or second in terms of absolute distance from 1.0. This is not surprising. Rank exponent weights guarantee that the weight to the most important dimension will be correct and thus the regression analysis will have an upper end point that is anchored to the correct ratio weight. It is interesting to note that in each comparison between rank reciprocal and rank sum

TABLE 7

Slopes based on regression of approximate weights on ratio weights.

	Rank Sum	Rank Reciprocal	Rank Exponent
<u>1st Level</u>	.641	.955*	1.101
<u>2nd Level</u>			
A Branch	1.551	2.279	1.005
B Branch	1.078*	1.815	1.159
C Branch	.861*	1.214	.996
D Branch	1.136*	1.244	.944
E Branch	1.002*	1.367	1.165
F Branch	.806*	1.376	1.208

*Weighting procedure selected by the decision rule rank procedure.
(For branch A the decision rule rank procedure led to the selection
of equal weights.)

weights, the decision rule procedure would have chosen the weighting technique whose slope was closest to 1.0. In addition, for the case in which the decision rule procedure indicated equal weights, both rank sum and rank reciprocal weights were much too peaked (indicated by slopes much higher than 1.0).

<u>III. B. Nuclear waste disposal site selection</u>

Otway and Edwards (1977) presents Multi-Attribute Utility Measurement (MAUM) as a method of evaluating proposed nuclear waste disposal sites. The paper demonstrates the usefulness of MAUM in combining technical information with the corresponding social attitudes. Although aware of the importance of these attitudes, technical experts typically have been unable either to measure them or to aggregate them with technical data. In the past, either or both of these problems have led the experts to make recommendations that overweight the importance of the engineering aspects of the problem. Of special interest is the recent development of methodologies for the measurement of social attitude toward technologies (Otway and Fishbein, 1976), hopefully solving the measurement problem. MAUM, of course, provides a means of aggregation.

The experts whose information was used for the analysis were ten high ranking specialists from eight countries with advanced nuclear energy programs. They were assembled for an international meeting concerned with nuclear waste disposal. The experts were very much concerned with the problems of disposal and the risks involved and were thus highly co-operative.

TABLE 8

Description of Six Hypothetical Nuclear Waste Disposal Sites

Value Dimension, Range and Scaling	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6
D1. Public attitude. 0 = extremely negative; 100 = extremely positive	40	20	10	40	60	70
D2. Remoteness from population center, km. (0 km = 0; 160 km = 100	40	12	12	120	40	120
D3. Geospheric path length, km (0 km = 0; 160 km = 100)	40	12	12	4	4	40
D4. Proximity to natural resources, km. (0 km = 0; 160 km = 100)	50	150	50	50	15	15
D5. Geologic disturbance probability per year (1 = 0; 10^{-6} = 100; linear in exponent)	10^{-4}	10^{-5}	10^{-4}	10^{-6}	10^{-5}	10^{-6}
D6. Relative migration rate of critical nuclide (1 = 0; 10^{-5} = 100; linear in exponent)	10^{-3}	10^{-3}	10^{-2}	10^{-1}	10^{-2}	10^{-1}
D7. Transportation distance km. (1600 km = 0; 0 km = 100)	1500	500	500	1500	150	150

Note: From "Application of a simple multiattribute rating technique to
evaluation of nuclear waste disposal sites: A demonstration." by
H.J. Otway and W. Edwards, International Institute for Applied Systems
Analysis Research Memorandum, 1977.

For the purposes of the analysis six hypothetical sites were invented.
One of the experts at the conference volunteered to perform this task.
He did so by thinking of real sites that, in the pasts, had been suggested
for the purpose. The relevant physical parameters were approximate
figures. Public attitudes toward the hypothetical waste disposal
sites were assigned on a random basis. Table 8 provides a numerical
description of sites.

As in the previous problem the SMART procedure was used in each
stage of the analysis. The experts described above provided the inputs.
In addition, the authors provided suggestions for dimensions, which the
experts accepted. These suggestions dealt primarily with public attitude.
Scaling of the location measures was also provided by the authors, but
in conjunction with the technical experts.

The final decision structure was not hierarchical. Each proposed
waste disposal site was evaluated on seven dimensions. They were:
public attitude toward the site remoteness form population center,
distance from the nearest point used by the public (called geospheric
path length by these nuclear specialists), proximity to natural resources,
geologic disturbance probability, relative migration rate of critical
nuclide, and the transportation distance between the site and the nuclear
plant it serves. All other dimensions were assumed equal for all sites
(for a discussion of nuclear waste disposal see Burkholder, 1976).

Importance weights of the value dimensions were judged twice. Thus, test-retest reliability of these judgments could be calculated. The authors perform these calculations and report a mean correlation of .93 with a standard deviation of .11. The lowest is .65. The second set of weights was used in the original analysis and will be used for the analyses in this paper. Correlations were also calculated between weights judged by all possible pairs of respondents for the second set of judgments. These were reported to range from .97 to -.27 with a mean of .39 and standard deviation of .35. Normalized averaged weights were then calculated across respondents and these means used in the utility analysis.

In order to examine the strength of Wainer's assertion that high negative correlations between dimensions occur rarely (Wainer, 1976), correlations were calculated for the values in this analysis. In seeming conflict with Wainer, some extremely high negative correlations occur. Over half (11 out of 21) interdimensional correlations are negative with several less then -.6 (see table 4, Otway and Edwards, 1977). Obviously some serious questions can be raised about the applicability of Wainer's result, at least for MAUM decision making contexts.

As originally scaled, the alternatives to be evaluated did not cover the full range of value on some attributes (see table 8). This is most striking for the third dimension, geospheric path length, where the range of the alternatives on that attribute covers only 22.5% of the range assigned to it. When a set of alternatives cover only a portion of the total range of an attribute the importance of that attribute is diminished proportionately (for linear utilities) to the part of the range not covered. That decrease is not represented in the original importance weight.

This problem can only be fully solved by judgmental methods; that is, reassessment of weights with attention to the range of values on alternatives. While a reassessment was not possible for this analysis, a transformation procedure was undertaken on the original weights in order to place all of the scaling value on the importance weighting. This placement is, of course, required for the use of rank weights. The transformation was as follows:

$$u'_{ij} = 100(u_{ij} - M_i)/R_i$$

$$W' = W_i R_i / S$$

where $S = \sum_i W_i R_i$.

R_i is the range of u_{ij} in dimension i over the set of entities to be evaluated, and M_i is the minimum value of u_{ij} over those entities in dimension i. So u'_{ij} will have a minimum value of 0 and a maximum of 100 on each dimension, over the set of entities to be evaluated.

Table 9 shows the transformed weights as well as the rank weight from each of the three rank weighting procedures. Equal weights would

give a weight of .143 to each of the seven dimensions. The decision rule weight selection procedure would lead to the use of rank sum weights.

This constitutes all the information necessary for the analysis. Each alternative was evaluated using each set of rank weights as well as equal weights and the original ratio weights elicited from the experts. As in the LASD analysis, Pearson correlations were calculated on values of overall utility between weighting techniques across potential sites. Overall utility calculated from ratio weighting correlated .86, .99, .72, and .97 with overall utility calculated from equal, rank sum,

TABLE 9

Weights elicited from experts and those from rank weighting procedures for Otway and Edwards (1977).

Value dimension	Transformed Ratio Weights	Rank Sum* Weights	Rank Reciprocal Weights	Rank Exponent Weights z= 1.62
Public Attitude	.246	.214	.193	.223
Distance from City	.087	.071	.064	.062
Geospheric Path Length	.088	.107	.077	.100
Proximity to Natural Resources	.267	.250	.386	.267
Earthquake Probability	.103	.143	.096	.139
Migration of Critical Nuclide	.153	.179	.129	.181
Transportation Distance	.055	.036	.055	.028

*Decision Rule Rank Weights would be the same as Rank Sum Weights

rank reciprocal and rank exponent weights respectively. For this
analysis both rank sum and rank exponent are markedly superior to equal
weights. It is especially interesting to note that the decision rule
procedure led to the selection of rank sum weights, clearly the optimal
choice from among the approximation procedures.

Kendall tau coefficients were calculated as in the previous
analysis. Tau was .733, .867, .333 and .733 between overall utilities
calculated from ratio weights and those calculated from equal, rank sum,
rank reciprocal and rank exponent weights respectively. Slopes were cal-
culated between ratio weights and each approximation weight set. Slopes
were .874, 1.27, and .990 between ratio weights and rank sum, rank reci-
procal and rank exponent weights respectively.

It seems apparent from a comparison of the correlations and slopes
that while rank sum weights prove superior for the alternatives in this
problem, it is quite likely that rank exponent weight would prove
superior generally. That is, for this analysis rank sum weighting
resulted in higher correlations between measures of overall utility
but rank exponent weights have slopes much closer to 1.0 and therefore
for a different set of alternatives would prove the superior procedure.

III. C. Automobile Selection.

A third brief example comes from work performed by J.R. Newman in
his reanalysis of a study of optimal automobile design. The Automobile
Club of Southern California developed a target program in which it sought
to evaluate the contribution of various factors or attributes to an
automobile's overall value to a cross section of the driving public.
The club's members and other experts provided the list of attributes.

Eleven attributes were identified consisting of fuel economy, interior size, passing/acceleration ability, interior noise, exterior size, crashworthiness, luggage capacity, handling, ride quality, ease of entry and exit and maneuverability.. Expert staff of the Auto Club itself provided location measures on each dimension. 31 non-dominated 1978 automobiles were used as alternatives for the anlaysis.

Interdimensional correlations were calculated. Correlations between attributes cover almost the full range from -1 to +1. Almost half (27 of 55) of the correlations are negative with 6 lower than -.6. As previously stated, these high negative correlations imply severe problems when equal weights are used for the analysis. This implied problem is illustrated by the comparison of the results from the various weighting schemes. Again Pearson correlations were calculated between weighting techniques, across alternatives. The correlations of ratio weighting with equal, rank sum, rank reciprocal, and rank exponent are .726, .800, .925, and .820 respectively. Equal weights clearly provide the worst approximation to the ratio weights. Rank sum and rank exponent are similar and rank reciprocal is by far the best approximation to ratio weights. As in the nuclear disposal site selection reanalysis the decision rule selection procedure results in a choice of the weighting technique that has the highest correlation with ratio weights.

Kendall tau coefficients between overall utilities were calculated along with slopes between weight sets. Tau was .588, .632, .788, and .600 between the results from ratio weights and those from equal, rank sum, rank reciprocal and rank exponent weights respectively. Slopes between ratio and rank sum, rank reciprocal and rank exponent were .685, 1.397 and 1.231.

The information provided by these two indices seems to be in conflict. While the slopes suggest that for the more general situation rank exponent weights would provide the best approximation, the correlations between measures of overall utility point to rank reciprocal (for this set of alternatives at least). Still, all of the rank weight procedures result in higher correlation than do equal weights, lending evidence for the use of some rank weighting procedure.

Discussion

The use of rank weighting techniques as approximations to ratio weights in this study provided remarkably good results. In each of the three reanalyses at least one of the rank weighting approximations resulted in a Pearson correlation coefficient between ratio and rank weights for aggregate overall utilities above .9. Also, in each of the re-analyses equal weighting of attributes led to a sizable loss in correlation for measures of overall value. Thus, rank weighting of attributes can be said to provide good approximations to the "true" ratio weights. Within the conditions of this study and for the purposes of multiattribute decision making, rank weights seem to be sufficient improvements over equal weights to warrant the extra effort involved in their elicitation.

Our ability to validate an approximation technique is obviously bounded by the quality of the judgment or value that is being approximated. Because this study depends so heavily on the ratio weights elicited from the subjects, some rationale should be developed for their use as a criterion. The use of ratio weights as a criterion rests on at least two assumptions. First, we are assuming that an individual knows his/her

own mind; that is, that he/she is able to determine the rank ordering of dimension importance, the relative strengths of the dimension weighting and a true zero point. Secondly, we are assuming that an individual can express this information in quantitative, orderly fashion.

Support for both of these assumptions comes from three studies. Each study examines weighting in the context of the multiple cue learning paradigm (Hammond and Summers, 1972). Cook and Stewart (1975), in a task where subjects were asked to evaluate graduate student profiles, found that: 1) various methods for elicitation of subjective weights (the weights that the subjects say they are using) result in roughly equivalent judgments, i.e., consensual validation, and 2) these subjective weights correspond fairly closely to objective weights derived from the best fit linear model (i.e., linear regression). Both of these conclusions suggest that subjects can express their decision policies in an orderly quantitative fashion.

Two other studies which lend support to the notion that subjects can accurately describe their decision policies are those of Schmitt (1978) and John and Edwards (Note 3). In each of these studies subjects were trained in a weighting model using the multiple cue learning paradigm (Hammond and Summers, 1972) and then asked to describe their subjective judgment as to the weighting of dimensions. Each study used a number of elicitation techniques for the report of these weights. In both of these studies the method of eliciting the subjective weight mattered little. More important, though, for the purposes of this discussion is the fact that both studies found a very strong relationship between predictions derived from the statistical model (regression model)

and those derived from subjects' subjective policy statements. Schmitt
sums up the findings of both studies when he says "The results also
suggest that weights in policy-capturing studies (e.g., Borman and
Dunnette, 1974) would not need to be statistical weights. The rational
judgments of cue weights are equally as good as the least-squares weights
derived from regressing subjects' judgments on the cues in the sense of
producing predicted values that correlate highly with optimal predic-
tions of the criterion of interest."

An additional point supporting the use of rank weighting approximations
involves the problems suggested for the use of equal weighting. The
correlations between attributes found in Otway and Edwards (1977) and
Newman (1978) raise serious doubts as to the stated generality of
conditions for the "equal weights theorem" detailed in Wainer (1976)
and expanded in Wainer (1978). Correlations were not calculated between
attributes for the LASD analysis. This was due to the complexity imposed
by the hierarchical MAUM structure. Values at any level of the hierarchy
were dependent on both weights and values from lower levels. In each of
the other two analyses, however, several dimensions correlated negatively
in excess of -.6. As previously stated, the frequency of the occurrence
of the high negative correlations in the two studies where examination was
possible suggest that Wainer's conclusions are not justified in view of the
severe and common violations of his condition.

In addition to the rank ordering of attributes, an additional bit
of information is required for two of the rank weighting techniques.
For rank exponent and decision rule rank weights, the proportion of the
total weight given to the most important dimension must be elicited from

the decision maker. For the purposes of these re-analyses it was assumed that the weight given to the first dimension by ratio weights was the correct weight for that dimension. Clearly, whether subjects can provide estimates of this quantity is an empirical question.

Work in progress will seek to test this question. Using an external criterion of utility weighting, this work will test rank weighting procedures against both the established "true" weight and the weights derived from subjects' judgments of those "true" weights. If in fact subjects can provide estimates of the most important dimension's weight which are both reliable and congruent with the established "true" weights, the results of the current study indicate that a simple decision rule strategy for selection of weight approximation procedure is remarkably effective for decision purposes. In each of the two analyses where one level of attributes was involved, the simple decision rule procedure for selection between equal, rank sum, rank reciprocal and ratio weighting led to selection of the technique which correlated highest with the results of ratio weighting. For the LASD analysis, the use of the decision rule strategy on each level of the hierarchy led to a remarkably good approximation of the analysis using the entire set of elicited ratio weights. The quality of this approximation (Pearson $r = .996$) is so good as to indicate that the effort involved in the elicitation of over 150 ratio weights was unnecessary and the decision rule rank weighting procedure a more than adequate approximation. In addition, rank exponent weights seem to consistently provide estimates of the ratio weights which have near the same level of peakedness. Looking at the regression analyses between the set of ratio weights and rank exponent weights for each

problem we found that slopes were generally near the correct 1.0.
This finding suggests that rank exponent weights will provide good
approximations to ratio weights in most instances.

The other possibility is that judges will not be able to reliably
provide the weight to the most improtant dimension.   In this case we
still find that the rank sum procedure provides an approximation that
is better than equal weights. In sum, we have a situation where rank
weighting has been shown to be superior to equal weights throughout
the reanalyses conducted in this paper. This is true whether or not
the more stringent assumptions necessary for the use of the decision
rule and the rank exponent weighting procedures are justified. Certainly,
the moderate increase in effort necessary for the elicitation of rank
ordering of dimensions is justified.

Reference Notes

1. Seaver, D.A. Correlation Analyses of Approximations and Sensitivity
    for Multi-Attribute Utility. Unpublished Manuscript, Mathematical
    Psychology Program, University of Michigan, 1973. Dr. Seaver
    may be contacted at the Decision Science Consortium, Reston,
    Virginia.

2. Edwards, W. Multi-Attribute Utility Measurement in a Highly Political
    Context: Evaluating Desegregation Plans in Los Angeles. Unpublished
    Manuscript, Social Science Research Institute, University of
    Southern California, 1978.

3. John, R. S. and Edwards, W. Elicitation of Importance Weights for
    Additive, Riskless Preference Functions: A Criterion Validation.
    Social Science Research Institute Technical Report, in preparation,
    University of Southern California, 1979.

References

Borman, W. C. and Dunnett, M. D. <u>Selection of components to comprise a naval personnel status index and a strategy for investigating their relative importance</u>. Minneapolis, MN: Personnel Decisions, 1974.

Burkholder, H. C. Methods and data for predicting nuclide migration in geologic media, <u>proceedings of the international symposium on the management of wastes from the LWR fuel cycle</u>, conference - 76-0701, U.S. Energy Research and Development Administration.

Conger, A. J. A revised definition for suppressor variables. A guide to their identification and interpretation. <u>Ed. and Psych Measurement</u>, <u>34</u>, 35-26, 1974

Cook, R. L. and Stewart, T. R. A comparison of seven methods for obtaining subjective descriptions of judgmental policy. <u>OBHP</u>, <u>13</u>, 31-45, 1975.

Dawes, R. M. A case study of graduate admissions: Application of three principles of human decision making. <u>Amer. Psychologist</u>, <u>26</u>, 180-187, 1971.

Edwards, W. Social utilities. <u>The Engineering Economist</u>, Summer symposium series, <u>6</u>, 119-129, 1971.

Edwards, W. How to use multiattribute utility measurement for social decision making. <u>IEEE Transactions on Systems, Man, and Cybernetics</u>, <u>Vol. SMC-7, No. 5</u>, 326-340, 1977.

Edwards, W., Guttentag, M., and Snapper, K. A decision-theoretic approach to evaluation research. In <u>Handbook of Evaluation Research</u>. (Elmer L. Struning and Marcia Guttentag, Editors) 1977.

Edwards, W., John, R. and Stillwell, W. G. Research on the technology of inference and decision. Social Science Research Institute technical report 77-6, University of Southern California, 1977.

Einhorn, H. and Hogarth, R. Unit weighting schemes for decision making. <u>OBHP</u>, <u>13,</u> 171-192, 1975.

Hammond, K. R. and Summers, D. A. Cognitive control. <u>Psych. Rev.</u>, <u>79</u>, 58-67, 1971.

Hays, W. L. <u>Statistics for</u> the Social Sciences. 2nd Edition. New York: Holt, Rinehart and Winston, 1963.

Laughlin. J. E. Comment on "estimating coefficients in linear models: It don't make no nevermind." Psych. Bull., 85, 247-253, 1978.

Keeney, R. L, and Raiffa, H. Decisions with Multiple Objectives: Preferences and Value Tradeoffs. John Wiley & Sons, 1976.

Keren, G. and Newman, J. R. Additional considerations with regard to Multiple Regression and Equal Weighting. OBHP (in press), 1979.

McClelland, G. H. Equal versus differential weighting for multi-attribute decisions: There are no free lunches. Report #207, Center for Research on Judgment and Policy, University of Colorado, 1978.

Newman, J. R. Differential weighting in multiattribute utility measurement: When it should not and when it does make a difference. OBHP, 20, 321-325, 1977.

Newman, J. R., Seaver, D. A. and Edwards, W. Unit versus differential weighting schemes for decision making: A method of study and some preliminary results. Social Science Research Institute technical report #76-5, University of Southern California, 1976.

Otway, H. H. and Edwards , W. Application of simple multiattribute rating technique to evaluation of nuclear waste disposal sites: A demonstration. Research report RM-77-31, International Institute for Applied Systems Analysis, Laxenburg, Austria, 1977.

Otway, H. J. and Fishbein, M. The determinants of attitude formation: An application to nuclear power, RM-76-80, International Institute for Applied Systems Analysis, Laxenburg, Austria, 1976.

Pruzek, R. M. and Frederick, B. C. Weighting predictors in linear models: Alternatives to least squares and limitations of equal weights. Psych. Bull., 85, 254-266, 1978.

Schmitt, N. Comparison of subjective and objective weighting strategies in changing task situations. OBHP, 24, 171-188, 1978.

Wainer, H. Estimating coefficients in linear models: It don't make no nevermind. Psych. Bull., 83, 213-217, 1976.

Wainer, H. On the sensitivity of regression and regressors. Psych. Bull., 85, 267-273, 1978.

CONTRACT DISTRIBUTION LIST
(Unclassified Technical Reports)

Director   2 copies
Advanced Research Projects Agency
Attention: Program Management Office
1400 Wilson Boulevard
Arlington, Virginia 22209

Office of Naval Research   3 copies
Attention: Code 455
800 North Quincy Street
Arlington, Virginia 22217

Defense Documentation Center   12 copies
Attention: DDC-TC
Cameron Station
Alexandria, Virginia 22314

DCASMA Baltimore Office   1 copy
Attention: Mr. K. Gerasim
300 East Joppa Road
Towson, Maryland 21204

Director   6 copies
Naval Research Laboratory
Attention: Code 2627
Washington, D.C. 20375

SUPPLEMENTAL DISTRIBUTION LIST
(Unclassified Technical Reports)

Department of Defense

Director of Net Assessment
Office of the Secretary of Defense
Attention: MAJ Robert G. Gough, USAF
The Pentagon, Room 3A930
Washington, DC 20301

Assistant Director (Net Technical Assessment)
Office of the Deputy Director of Defense
  Research and Engineering (Test and
  Evaluation)
The Pentagon, Room 3C125
Washington, DC 20301

Director, Defense Advanced Research
  Projects Agency
1400 Wilson Boulevard
Arlington, VA 22209

Director, Cybernetics Technology Office
Defense Advanced Research Projects Agency
1400 Wilson Boulevard
Arlington, VA 22209

Director, ARPA Regional Office (Europe)
Headquarters, U.S. European Command
APO New York 09128

Director, ARPA Regional Office (Pacific)
Staff CINCPAC, Box 13
Camp H. M. Smith, Hawaii 96861

Dr. Don Hirta
Defense Systems Management School
Building 202
Ft. Belvoir, VA 22060

Chairman, Department of Curriculum
  Development
National War College
Ft. McNair, 4th and P Streets, SW
Washington, DC 20319

Defense Intelligence School
Attention: Professor Douglas E. Hunter
Washington, DC 20374

Vice Director for Production
Management Office (Special Actions)
Defense Intelligence Agency
Room 1E863, The Pentagon
Washington, DC 20301

Command and Control Technical Center
Defense Communications Agency
Attention: Mr. John D. Hwang
Washington, DC 20301

Department of the Navy

Office of the Chief of Naval Operations
  (OP-951)
Washington, DC 20450

Office of Naval Research
Assistant Chief for Technology (Code 200)
800 N. Quincy Street
Arlington, VA 22217

Office of Naval Research (Code 230)
800 North Quincy Street
Arlington, VA 22217

Office of Naval Research
Naval Analysis Programs (Code 431)
800 North Quincy Street
Arlington, VA 22217

Office of Naval Research
Operations Research Programs (Code 434)
800 North Quincy Street
Arlington, VA 22217

Office of Naval Research
Information Systems Program (Code 437)
800 North Quincy Street
Arlington, VA 22217

Director, ONR Branch Office
Attention: Dr. Charles Davis
536 South Clark Street
Chicago, IL 60605

Director, ONR Branch Office
Attention: Dr. J. Lester
495 Summer Street
Boston, MA 02210

Director, ONR Branch Office
Attention: Dr. E. Gloye
1030 East Green Street
Pasadena, CA 91106

Director, ONR Branch Office
Attention: Mr. R. Lawson
1030 East Green Street
Pasadena, CA 91106

Office of Naval Research
Scientific Liaison Group
Attention: Dr. M. Bertin
American Embassy - Room A-407
APO San Francisco 96503

Dr. A. L. Slafkosky
Scientific Advisor
Commandant of the Marine Corps (Code RD-1)
Washington, DC 20380

Headquarters, Naval Material Command
(Code 0331)
Attention: Dr. Heber G. Moore
Washington, DC 20360

Dean of Research Administration
Naval Postgraduate School
Attention: Patrick C. Parker
Monterey, CA 93940

Superintendent
Naval Postgraduate School
Attention: R. J. Roland, (Code 52R1)
           C^3 Curriculum
Monterey, CA 93940

Naval Personnel Research and Development
  Center (Code 305)
Attention: LCDR O'Bar
San Diego, CA 92152

Navy Personnel Research and Development
  Center
Manned Systems Design (Code 311)
Attention: Dr. Fred Muckler
San Diego, CA 92152

Naval Training Equipment Center
Human Factors Department (Code N215)
Orlando, FL 32813

Naval Training Equipment Center
Training Analysis and Evaluation Group
  (Code N-00T)
Attention: Dr. Alfred F. Smode
Orlando, FL 32813

Director, Center for Advanced Research
Naval War College
Attention: Professor C. Lewis
Newport, RI 02840

Naval Research Laboratory
Communications Sciences Division (Code 54
Attention: Dr. John Shore
Washington, DC 20375

Dean of the Academic Departments
U.S. Naval Academy
Annapolis, MD 21402

Chief, Intelligence Division
Marine Corps Development Center
Quantico, VA 22134

Department of the Army

Deputy Under Secretary of the Army
(Operations Research)
The Pentagon, Room 2E611
Washington, DC 20310

Director, Army Library
Army Studies (ASDIRS)
The Pentagon, Room 1A534
Washington, DC 20310

U.S. Army Research Institute
Organizations and Systems Research Laboratory
Attention: Dr. Edgar M. Johnson
5001 Eisenhower Avenue
Alexandria, VA 22333

Director, Organizations and Systems
  Research Laboratory
U.S. Army Institute for the Behavioral
  and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

Technical Director, U.S. Army Concepts
  Analysis Agency
8120 Woodmont Avenue
Bethesda, MD 20014

Director, Strategic Studies Institute
U.S. Army Combat Developments Command
Carlisle Barracks, PA 17013

Commandant, Army Logistics Management Center
Attention: DRXMC-LS-SCAD (ORSA)
Ft. Lee, VA 23801

Department of Engineering
United States Military Academy
Attention: COL A. F. Grum
West Point, NY 10996

Marine Corps Representative
U.S. Army War College
Carlisle Barracks, PA 17013

Chief, Studies and Analysis Office
Headquarters, Army Training and Doctrine
  Command
Ft. Monroe, VA 23351

Commander, U.S. Army Research Office
  (Durham)
Box CM, Duke Station
Durham, NC 27706

Department of the Air Force

Assistant for Requirements Development
  and Acquisition Programs
Office of the Deputy Chief of Staff for
  Research and Development
The Pentagon, Room 4C331
Washington, DC 20330

Air Force Office of Scientific Research
Life Sciences Directorate
Building 410, Bolling AFB
Washington, DC 20332

Commandant, Air University
Maxwell AFB, AL 36112

Chief, Systems Effectiveness Branch
Human Engineering Division
Attention: Dr. Donald A. Topmiller
Wright-Patterson AFB, OH 45433

Deputy Chief of Staff, Plans, and
  Operations
Directorate of Concepts (AR/XOCCC)
Attention: Major R. Linhard
The Pentagon, Room 4D 1047
Washington, DC 20330

Director, Advanced Systems Division
  (AFHRL/AS)
Attention: Dr. Gordon Eckstrand
Wright-Patterson AFB, OH 45433

Commander, Rome Air Development Center
Attention: Mr. John Atkinson
Griffis AFB
Rome, NY 13440

IRD, Rome Air Development Center
Attention: Mr. Frederic A. Dion
Griffis AFB
Rome, NY 13440

HQS Tactical Air Command
Attention: LTCOL David Dianich
Langley AFB, VA 23665

Other Government Agencies

Chief, Strategic Evaluation Center
Central Intelligence Agency
Headquarters, Room 2G24
Washington, DC 20505

Director, Center for the Study of
   Intelligence
Central Intelligence Agency
Attention: Mr. Dean Moor
Washington, DC 20505

Mr. Richard Heuer
Methods & Forecasting Division
Office of Regional and Political Analysis
Central Intelligence Agency
Washington, DC 20505

Office of Life Sciences
Headquarters, National Aeronautics and
   Space Administration
Attention: Dr. Stanley Deutsch
600 Independence Avenue
Washington, DC 20546

Other Institutions

Department of Psychology
The Johns Hopkins University
Attention: Dr. Alphonse Chapanis
Charles and 34th Streets
Baltimore, MD 21218

Institute for Defense Analyses
Attention: Dr. Jesse Orlansky
400 Army Navy Drive
Arlington, VA 22202

Director, Social Science Research Institute
University of Southern California
Attention: Dr. Ward Edwards
Los Angeles, CA 90007

Perceptronics, Incorporated
Attention: Dr. Amos Freedy
6271 Variel Avenue
Woodland Hills, CA 91364

Stanford University
Attention: Dr. R. A. Howard
Stanford, CA 94305

Director, Applied Psychology Unit
Medical Research Council
Attention: Dr. A. D. Baddeley
15 Chaucer Road
Cambridge, CB 2EF
England

Department of Psychology
Brunel University
Attention: Dr. Lawrence D. Phillips
Uxbridge, Middlesex UB8 3PH
England

Decision Analysis Group
Stanford Research Institute
Attention: Dr. Miley W. Merkhofer
Menlo Park, CA 94025

Decision Research
1201 Oak Street
Eugene, OR 97401

Department of Psychology
University of Washington
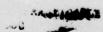Attention: Dr. Lee Roy Beach
Seattle, WA 98195

Department of Electrical and Computer
   Engineering
University of Michigan
Attention: Professor Kan Chen
Ann Arbor, MI 94135

Department of Government and Politics
University of Maryland
Attention: Dr. Davis B. Bobrow
College Park, MD 20747

Department of Psychology
Hebrew University
Attention: Dr. Amos Tversky
Jerusalem, Israel

Dr. Andrew P. Sage
School of Engineering and Applied
   Science
University of Virginia
Charlottesville, VA 22901

Professor Raymond Tanter
Political Science Department
The University of Michigan
Ann Arbor, MI 48109

Professor Howard Raiffa
Morgan 302
Harvard Business School
Harvard University
Cambridge, MA 02163

Department of Psychology
University of Oklahoma
Attention: Dr. Charles Gettys
455 West Lindsey
Dale Hall Tower
Norman, OK 73069

Institute of Behavioral Science #3
University of Colorado
Attention: Dr. Kenneth Hammond
Room 201
Boulder, Colorado 80309

Decisions and Designs, Incorporated
Suite 600, 8400 Westpark Drive
P.O. Box 907
McLean, Virginia 22101

REPORT DOCUMENTATION PAGE

1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
001595-2-T		

4. TITLE (and Subtitle)	5. TYPE OF REPORT & PERIOD COVERED
Rank Weighting in Multiattribute Utility Decision Making: Avoiding the Pitfalls of Equal Weights	Technical 12/78 - 12/79
	6. PERFORMING ORG. REPORT NUMBER 79 - 2

7. AUTHOR(s)	8. CONTRACT OR GRANT NUMBER(s)
William G. Stillwell Ward Edwards	N00014-79-C-0038

9. PERFORMING ORGANIZATION NAME AND ADDRESS	10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
Social Science Research Institute University of Southern California Los Angeles, California 90007	

11. CONTROLLING OFFICE NAME AND ADDRESS	12. REPORT DATE
Office of Naval Research - Dept. of the Navy 800 N. Quincy Street Arlington, VA 22217	September, 1979
	13. NUMBER OF PAGES 35

14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)	15. SECURITY CLASS. (of this report)
Office of Naval Research Research Branch Office 1030 East Green Street Pasadena, California 91101	unclassified
	15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

rank weights   rank order
equal weighting
decision models
Kendall tau coefficient

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

The notion of dominance in multiattribute utility decision contexts leads to a change in the considered alternative set. The implications of this set change are discussed in relation to the conditions of Wainer's (Wainer, 1976)"equal weights theorem" and the resulting sensitivity to weighting of importance dimensions demonstrated. Data from three multiattribute decision making studies are examined using four rank weighting techniques as well as equal weights. Rank weighting of importance dimensions demonstrate marked improvement of approximation as reflected in both Pearson and rank order correlations for measures

DD FORM 1473 1 JAN 73   EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102-014-6601

unclassified

of overall utility across alternatives within the nondominated subset.
Implications for multiattribute utility application are discussed.